

A Spine X-Ray Image Retrieval System Using Partial Shape Matching

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Abstract—In recent years, there has been a rapid increase in the size and number of medical image collections. Thus, the development of appropriate methods for medical information retrieval is especially important. In a large collection of spine X-ray images, maintained by the National Library of Medicine, vertebral boundary shape has been determined to be relevant to pathology of interest. This paper presents an innovative partial shape matching (PSM) technique using dynamic programming (DP) for the retrieval of spine X-ray images. The improved version of this technique called corner-guided DP is introduced. It uses nine landmark boundary points for DP search and improves matching speed by approximately 10 times compared to traditional DP. The retrieval accuracy and processing speed of the retrieval system based on the new corner-guided PSM method are evaluated and included in this paper.

Index Terms—Corner-guided, dynamic programming, image retrieval, National Health and Nutrition Examination Survey (NHANES II), partial shape matching.

I. INTRODUCTION

THERE has been growing interest in content-based indexing of biomedical images, especially for developing an automated or a computer-aided interactive medical information retrieval system. A digital archive of 17 000 cervical and lumbar spine X-ray images from the second National Health and Nutrition Examination Survey (NHANES II) is maintained by the Lister Hill National Center of Biomedical Communications at National Library of Medicine (NLM) at the National Institutes of Health (NIH). An interactive retrieval system for these X-ray images is important for research purposes, including finding pathological exhibits in a large survey collection, and education purposes including training medical students, etc. Another very important application is to provide reference to radiologists to assist diagnosis. Research work has been done to index

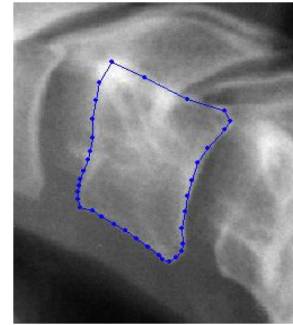


Fig. 1. X-ray image with the superimposed blue (or dark dotted line in black and white) shape contour. Shape contour has been proven to be the best feature to use.

and retrieve these images. We have developed query-by-sketch- and query-by-example-based methods for shape-based image retrieval, which offers visual search of these images. The development of a more powerful and user-friendly system is an ongoing project at the NLM. The latest revision of this system supports hybrid image and text queries [1], [2].

Content-based image retrieval (CBIR) remains an active research area seeking representation methods and retrieval algorithms for color, shape, and texture. Fig. 1 shows a spine X-ray image with the segmented shape contour. As shown, spine X-ray images generally have low contrast and poor image quality. In these images, no meaningful texture information exists. The shape, however, effectively describes various pathologies identified by medical experts as being consistently and reliably found in this image collection. About 4500 cervical and lumbar shapes have been segmented from over 900 images in the collection using an active contour-based algorithm that uses orthogonal curves [3]. Despite the automated nature of the segmentation algorithm, manual intervention was occasionally necessary due to poor image quality.

Shape matching is a well-explored research area with many shape representation and similarity measurement techniques found in the literature [4]–[15]. Shape representation methods include Fourier descriptors [4]–[6], polygonal approximation [7], invariant moments [8], [9], B-splines [10], [11], deformable templates [12], and curvature scale space (CSS) [13], [14]. Most of these techniques were developed for whole shape matching, i.e., closed planar curve matching. The CSS shape representation method has been selected for moving picture experts group (MPEG)-7 standardization [13], [14], [16]. However, based on the curvature zero-crossing, the CSS method is more suitable for shapes with distinct curvature variations, such as leaf shapes

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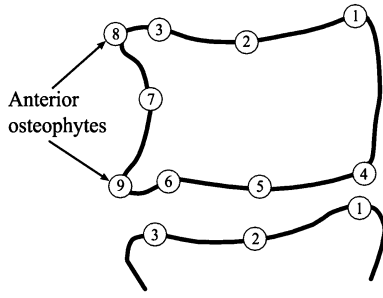


Fig. 2. Radiologist marked 9-point model for vertebral shape description. Points 8 and 9, if not coincident with points 3 and 6, respectively, indicate the existence of osteophytes.

than for smooth shapes with subtle curvature variations. Fourier descriptor has proven to be more efficient and robust than is the CSS in a review of shape representation and description techniques [15]. But, as mentioned in [15], Fourier descriptor was not suitable for partial shape matching.

Our previous research work focused on the whole shape matching for spine shapes [17]–[19]. Several different methods including Fourier descriptors, polygonal approximation, geometric global shape properties (such as eccentricity, elongation, etc.), and invariant moments were implemented and evaluated for spine X-ray retrieval. However, whole shape matching techniques provided relatively low retrieval accuracy in retrieving similar pathological spine shapes.

For spine shapes, pathologies found on the spine X-ray images that are of interest to the medical researchers are generally expressed along the vertebral boundary. These pathologies include anterior osteophytes (AOs), intervertebral disc degeneration, and resulting disc space narrowing, spondylolisthesis, and spondylololsthesis. Among them, work presented in this paper focuses on AOs that show up on the two anterior “corners” in the sagittal view, and the deformation appears as a protrusion, as shown in Fig. 2.

In terms of AO pathology, therefore, there are critical intervals along the vertebral boundary that the radiologist would focus on rather than the whole shape. This indicates the main drawback of the whole shape matching: *certain parts on the vertebra shape that are not of pathological interest may obscure the differences between critical regions, and thus, hinder accurate retrieval.*

Partial shape matching (PSM) was investigated as an alternative to whole shape matching and to enable retrieval specific to the pathology on the anatomy of interest. In general, there is very little information in the literature on the application of partial shape matching for retrieval of medical images. It allows querying on some specific intervals along the vertebral boundary shape and searches for the best matching intervals on other whole shapes. This PSM concept theoretically addresses the same problem as *region-based* image retrieval, which divides the whole image into several regions and weighs regions on their significance [20], [21].

PSM also provides a way to deal with occlusion and distortion when comparing two incomplete shapes or distorted shapes [22]–[26]. Different shape representations such as wedge

wave, inflection points, and line segments were used. The recent contribution by Petrakis *et al.* [25] presented an approach for open shape matching using DP. Inflection points served as inputs to the shape representation method. The extracted shape features included the length, the area, and the rotation angle. DP selects the most promising candidate points to merge in its search for the match path with the least cost (highest similarity). Allowing merging points made this approach capable of addressing the matching problems in the presence of occlusion and distortion. However, inflection points are not suitable for rectangular spine shapes since a rectangular shape does not have a significant number of inflection points. Gdalyahu *et al.* constructed a syntactic shape representation, whose primitives were line segments and whose attributes were length and absolute orientation [24]. The search was also achieved by using DP.

Arica *et al.* introduced a perceptual shape descriptor [26]. Each point on the boundary was represented by the moments of the angles, each of which was formed by a pair of the bearings at a boundary point. The limitation of this method is that it requires uniformly distributed shape data points. Shape data points for our application are not equally distributed because dense data points are needed to better describe the pathological details of the region of interest, e.g., the AO regions shown in Fig. 2. In other words, the AO regions need to be represented with more data points than other regions on a spine shape.

More often, shapes are represented by different numbers of points, different data point distributions or data sample spacing, which is the case for the spine shapes in our database. Also, noise may occur during the process of contour segmentation. Thus, the capability of merging data points that DP possesses is preferred.

Based on the perceptual shape descriptor in [26], we developed a multiple open triangle shape representation method, which does not require equally distributed shape data points. A line segment method with two old attributes (length and absolute orientation) [24] and one new attribute (relative orientation) was also implemented for comparison. The DP was implemented for both shape representations as our initial PSM work [27].

A high computational requirement is a significant drawback of DP, especially for a large medical image database. Based on the rectangular nature of spine shapes and the 9-point landmark model, corner-guided PSM using DP is proposed and presented in this paper. Limiting the possible search regions to four corners dramatically increases the search speed. An innovative approach has been taken to modify the traditional DP to perform matching, starting from a corner, which is a point in the middle of the whole matching segment, rather than from the first point of the matching segment.

In this paper, we will start Section II with an introduction of the nine point landmark model that radiologists use to describe vertebral shapes. We will then introduce our algorithm capable of automatically locating the 9-point model. Section III will focus on PSM and the improved corner-guided PSM using the modified DP. The retrieval system based on PSM as well as the retrieval performance evaluation will be discussed in Section IV. Our conclusions will appear in Section V.

II. 9-POINT MODEL

Fig. 2 shows a nine morphometric landmark-point model schematic. Points 8 and 9 indicate the existence of AO. For normal vertebrae, points 8 and 9 will coincide with points 3 and 6, respectively. The 9-point model helps radiologists and bone morphometrists in marking relevant pathology on spine X-ray images. The semantic relevance of the 9 points in the sagittal view is as follows.

- 1) Points 1 and 4 mark the upper and lower posterior “corners” of the vertebra, respectively.
- 2) Points 3 and 6 mark the upper and lower anterior “corners” of the vertebra, respectively.
- 3) Points 2 and 5 are the median along the upper and lower vertebra edge.
- 4) Point 7 is the median along the anterior vertical edge of the vertebra.
- 5) Points 8 and 9 indicate the presence of the upper and lower anterior osteophytes, respectively. These points are typically marked at the osteophyte extremities.

We have developed an algorithm for automatic localization of these points by applying heuristics based on their semantic relevance [28]. This auto-localization algorithm provides the corner information for our proposed corner-guided PSM using DP, and thus, is an essential part of the retrieval system. The corner detection part of the 9-point localization algorithm is included as follows, and more details can be found in our earlier paper [28].

Curve evolution technique [29], [30] was implemented to reduce the number of data points while keeping the most significant ones. This is achieved by iteratively comparing a relevance measure expressed in (1) of all remaining vertices on the shape

$$K(s_1, s_2) = \frac{|(\beta(s_1, s_2) - 180)| l(s_1) l(s_2)}{l(s_1) + l(s_2)} \quad (1)$$

where $\beta(s_1, s_2)$ is the angle between two adjacent line segments s_1 and s_2 , and $l(s_1)$ and $l(s_2)$ represent the normalized length (to the total length of the whole shape) of s_1 and s_2 , respectively. Higher relevance value means that the vertex has larger contribution to the shape of the curve. The angle $\beta(s_1, s_2)$ was calculated as the outer angle between two line segments. The curve evolution stopped when the number of remaining vertices was down to 20. The bend angle, as illustrated in Fig. 3 was then calculated for each of these 20 points, and it was calculated in a way so that the clockwise turn gives a negative angle, whereas a counterclockwise turn gives a positive angle. Thus, only the vertices with a positive bend angle can be a corner. The corners were detected according to the following rules.

- 1) Vertices with a negative angle will be removed.
- 2) If there are two adjacent vertices and both with a positive bend angle, the vertex with the smaller bend angle will be removed.
- 3) If there are more than four points left, sequentially connect all remaining vertices, recalculate their bend angles, and then repeat steps 1 and 2.

The auto-localization algorithm has been tested on a subset of 250 vertebral shapes from those marked by a board certified

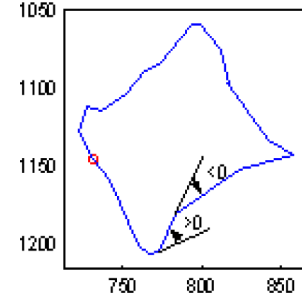


Fig. 3. Bend angle.

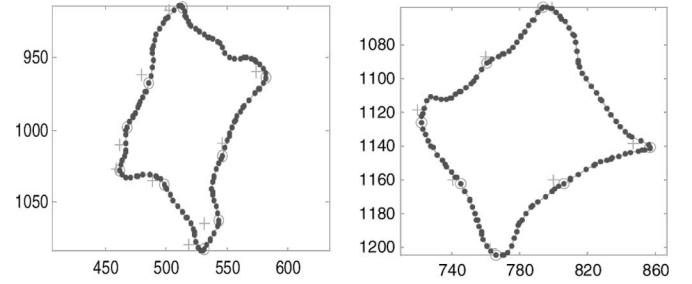


Fig. 4. Auto-localization of 9-point model. The crosses represent the expert marked points and the circles represent the points our algorithm detected.

radiologist. An evaluation was done by comparing automatic localization results with that of expert marked points. As shown in Fig. 1, spine contours in X-rays typically have a broad edge. This inevitably induces the slight difference between the visual contours on the images and the segmented spine shapes, even though the segmented shapes well retain the spine silhouettes. Fig. 4 shows two samples of the 9-point auto-localization algorithm's performance with one 7-point (without AO) and one 9-point (with AO). The crosses represent the points marked by the radiologist on the X-ray images and the circles represent the points localized by the algorithm on the spine shapes. As we have mentioned about the possible edge shift caused by the broad edge, the two sets of nine points are not identical. However, the algorithm performs fairly well in detecting the AOs and the corners. The minimum L_2 distance between the two sets of nine points was calculated to evaluate the accuracy of the algorithm. For 93% of the 250 tested shapes, the minimum distance was below 20 pixels, which we consider to be very impressive.

III. PARTIAL SHAPE MATCHING

A. Shape Representation Methods

1) *Line Segments*: A line segment is formed by connecting two adjacent points on the shape contour. Suppose a shape has N points: if it is closed, it has N line segments; if it is open, it has $N - 1$ line segments. Besides the two shape features (length and absolute orientation) used in [24], relative orientation is proposed as the third feature. They are described as follows.

- 1) Length: 2-norm of the line segment.

- of each individual possible matching path and get the first best matched open triangle with the lowest cost. For example, in Table II, points 4 and 7 on shape *B* are chosen to be the best match to points 1 and 4 on query *A*, respectively.
- 2) If one side reaches the termination area first, go to Step 4; otherwise, search for the next one line segment on both sides. The new cost part is produced by matching the second open triangle of the corner and the first open triangle of the two points selected in Step 1.
 - 3) If one side hits the termination area first, go to Step 4; otherwise, search for the next one line segment on both sides. The new cost part is produced by matching the third open triangle of the corner, the second open triangle of the two points selected in Step 1, and the first open triangle of both points selected in Step 2. Since the maximum number of open triangles associated with one point is limited to 3, this step completes the matching of all possible three open triangles associated with the corner.
 - 4) Take each side of the corner and continue the matching according to the traditional DP. Each side stops independently when it reaches the termination area. The whole matching finishes when both sides reach the corresponding termination area.

Corner-guided DP selects only four best matching paths for one individual object shape. However, the traditional DP selects a best matching path for every point on the object shape. Even though the time of completing a best matching path varies from point to point, the assumption that the time is equal can be made statistically. Thus, suppose an object shape has N points, the corner-guided DP will be $N/4$ times faster than the typical DP. So the more points the object shape has, the more efficient the corner-guided DP is compared to the traditional DP. This is a significant improvement, especially when retrieving images from a large database.

IV. SYSTEM, PERFORMANCE, AND EVALUATION

Fig. 7 shows the user interface of the retrieval system implemented in Matlab. “Load query” allows the user to select a spine shape from the database, which is shown in blue (solid line). “PSM select” allows the user to specify a specific region of interest on the whole shape, which is then highlighted in red (solid line with dots). The system provides two retrieval methods: corner-guided Procrustes [31] distance and corner-guided PSM with DP by using multiple open triangle representation. The Procrustes method performs a linear transformation (translation, rotation, and scaling) on one shape to find the best match between two shapes. Suppose (x, y) and (x', y') are n boundary point coordinates of shapes *A* and *B*, respectively. The Procrustes distance is then represented by (9), where shape *A* is translated by (T_x, T_y) , scaled by S , and rotated by θ

$$P = \sum_{i=1}^n \left\| \begin{bmatrix} S \cdot \cos \alpha & -\sin \alpha & T_x \\ \sin \alpha & S \cdot \cos \alpha & T_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}_A - \begin{bmatrix} x'_i \\ y'_i \\ 1 \end{bmatrix}_B \right\|^2. \quad (9)$$

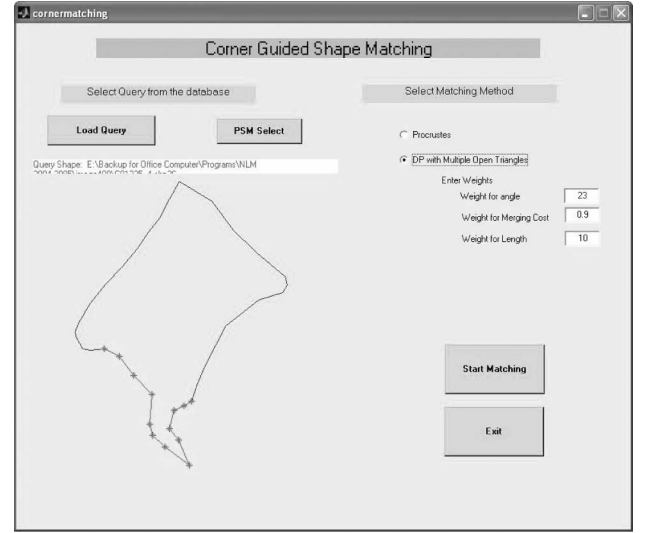


Fig. 7. System user interface. Users are allowed to select a query shape from the database and to highlight the partial shape as the region of interest.

The drawback of the Procrustes distance measure is that it requires the same number of points on the two partial/whole shapes. For corner-guided PSM method, the system provides a set of default values for the weights shown in (8), and also, the option for the user to specify different weights if so desired. A set of 801 cervical shapes and 972 lumbar shapes segmented from a total of 400 images has been chosen for performance evaluation. We used two interior corners of each of these 1773 shapes for study. These 3546 corners were classified as having server, moderate, or slight/normal AO pathology. Approximately 23.54% of these corners were considered with AO pathology (server or moderate). The rest of them were considered nonpathological. Ten queries (five cervical and five lumbar) were chosen, and the best 15 matches to each query were retrieved for study. Human relevance judgments were employed to evaluate the effectiveness of the two methods. Specifically, three human reviewers inspected the retrieval results of a query, and judged whether it was a similar match to the query.

Fig. 8 shows the retrieval results of a partial query using corner-guided PSM, while Fig. 9 gives the retrieval results of the same query using corner-guided Procrustes distance. As shown, corner-guided PSM performs better in detecting the details of the angle changes of the query. Since DP performs shape matching based on multiple open triangles, it extends the matching path line segment by line segment. Procrustes treats the partial query as a “whole shape” and performs the alignments globally to find the minimum distance. Thus, theoretically, DP is superior to Procrustes in detecting the details. Furthermore, DP allows merging data point and does not require the same number of points to match two partial shapes. This also enables DP to overcome noise on the contour by merging/removing noisy data points. Procrustes distance requires the same number of points to match the two shapes, and thus, cannot deal with noise or different point distributions. Fig. 10 shows the retrieval results of another query using corner-guided PSM.

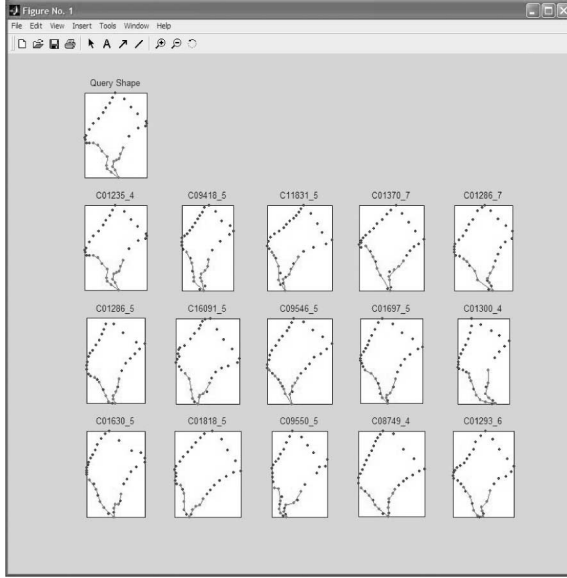


Fig. 8. Matching results by using the corner-guided PSM. The system retrieved 15 similar shapes from the database. Based on the human judgment and comparing with other shapes in the database, the system successfully retrieved the top 15 similar shapes.

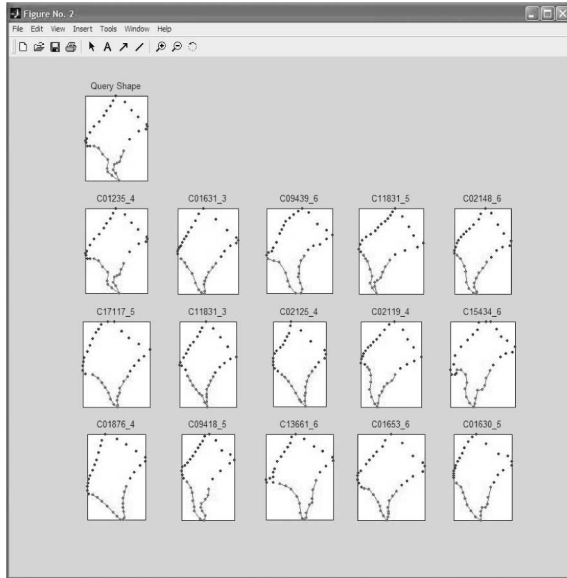


Fig. 9. Matching results by using corner-guided Procrustes distance measure. The system retrieved 15 similar shapes from the database using the same query shape as the one shown in Fig. 8. Based on the human judgment and comparing with other shapes in the database, the system incorrectly retrieved at least four shapes. The obvious errors are retrievals #3 and #11.

A simplified and common way of computing precision and recall was used to give a statistical evaluation of the corner-guided PSM method, corner-guided Procrustes distance, and the traditional DP method.

- 1) Precision is the percentage of qualifying shapes retrieved with respect to the total number of retrieved shapes.
- 2) Recall is the percentage of qualifying shapes retrieved with respect to the total number of similar shapes in the database.

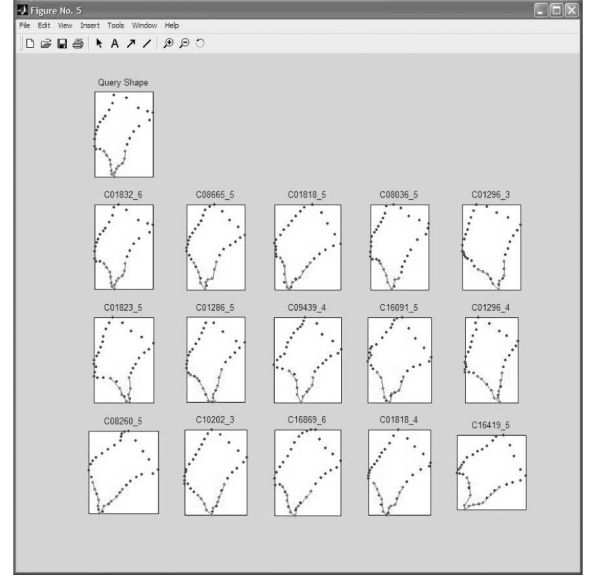


Fig. 10. Matching results of a different query using corner-guided DP. The system retrieved 15 similar shapes from the database. Based on the human judgment and comparing with other shapes in the database, the system successfully retrieved the top 15 similar shapes. The retrieval result seems to be slightly better than the one shown in Fig. 8.

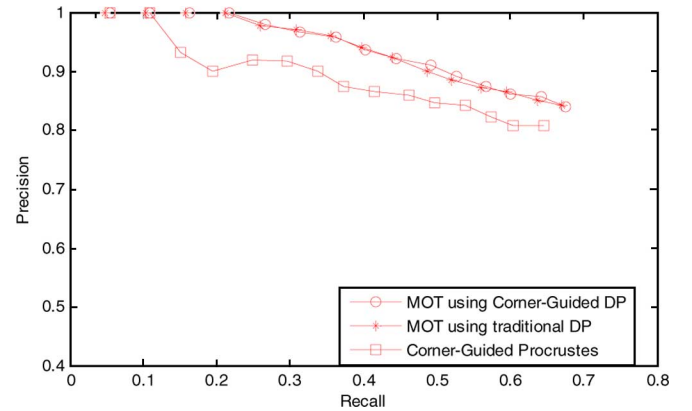


Fig. 11. Precision-recall results.

Because of the subjective nature of human vision, human relevance was used to provide the ground truth in most shape retrieval result evaluations [25]. Three human subjects contributed their judgment to the evaluation of this spine X-ray retrieval system. Due to the large volume of the database, it is very difficult to find all the similar shapes manually in the database for a specific query. Matches for all ten queries from half of the entire database were picked by human judges, and the assumption that there is equal number of similar shapes to a specific query in both halves of the database was made.

The precision-recall results are plotted in Fig. 11. The horizontal axis corresponds to the measured recall while the vertical axis corresponds to precision. The plot contains 15 points, which corresponds to 15 best matches and each point in the plot is the average of ten queries. The first point from the left of the plot corresponds to the average precision and recall values for the best match of the ten queries, while the second point from the left corresponds to the average precision and recall values for

the top two matches, and so on. Higher precision and higher recall represent better retrieval performance. The precision of the proposed corner-guided PSM using DP starts from 100% (successfully retrieves the top match for all ten queries) and drops down gradually as a larger number of matches are considered. For the ten queries we picked, the lowest precision of corner-guided PSM is still above 85%. And corner-guided PSM has a consistently higher precision than that of corner-guided Procrustes distance. Traditional DP, on the other hand, presents a very comparable precision with corner-guided PSM.

The time efficiency of these three methods was also examined. First, nine points of each shape in the database can be precalculated and stored. Therefore, the time for 9-point localization does not contribute to the following processing times. The average processing times for corner-guided PSM, corner-guided Procrustes, and traditional DP are 42, 19, and 400 s, respectively. Thus, compared to the traditional DP, corner-guided PSM using the modified DP speeds up the retrieval process by approximately ten times. Although corner-guided PSM is slower than Procrustes, its average processing time is feasible for an image retrieval system.

V. CONCLUSION

A spine X-ray image retrieval system has been described in this paper. According to the 9-point model and the shape nature of vertebral shapes, we introduced a corner-guided PSM method that uses a multiple open triangle shape representation method, and a modified DP for matching. This method is invariant to translation, scaling, rotation, and the starting point selection. Tested on retrieving 15 best matches for ten queries, this method has impressively high precision. With higher processing efficiency than that of the traditional DP approach, corner-guided PSM is a very promising and practical method for spine shape retrieval. The corner-guided PSM processing speed can be further improved if implemented with a more efficient programming language and development environment than the Matlab. The weights of merging cost, length, and the angle are adjustable by the user during the retrieval process. However, the user usually does not have the knowledge of how different weights can change the retrieval results. Thus, our future work includes building an interactive retrieval environment to allow the user to provide relevance feedback [32] so as to automatically adjust the weights to refine the retrieval results. The sensitivity of the retrieval method on these weights can also be examined during the relevance feedback process.

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